Date of notes: February 16, 2020
CAP 4600 All Notes

1.a. Slide Notes

- In terms of being a superset, AI → Machine learning → Deep learning.
- Symbolic AI (also called GOFAI): term for collection of all methods in AI based in symbolic representation.
- Diagram of above: input & rules → [machine] → output.
- ML programs adjust themselves in response to data they're exposed to.
- ML is dynamic and doesn't require human intervention to make certain changes.
- Diagram of ML: input & output → [machine] → rules.

1.b. Slide Notes

- ML has paradigms, mostly either through supervised or unsupervised learning.
- Supervised learning: ML where model is provided w/ labeled training data.
- Features and their corresponding labels are fed into an algorithm in the training process.
- The algorithm gradually determines the relationship btw. features and corresponding labels, called a model.
- Finding patterns btw. data and labels in supervised ML learning can be expressed mathematically as functions.
- Unsupervised learning: identifying meaningful patterns in data (and using that to understand the importance of new data).
- Reinforcment learning: at time step t, the agent is in state s_t, takes action a_t, receives reward r_t, and transitions into state s_{t+1}.
- Agent has to learn which actions to take at the current state for the maximum rewards.
- You also need to provide a way for the agent to interact w/ the game to produce data, physically or virtually.

2.a. Slide Notes

- Supervised ML learning terminology:
- Label: what we seek to predict.

- Feature x_j: input variable that is used to predict the label, where $j \in \{1, \ldots, n\}$ where n is the number of features.
- Many features can be used for projects requesting more regulation.
- Example: particular instance of data fed into models
- Labeled ex.: includes both features and the label, like: {features, label}: (x,y)
  - Used to train model.
- Unlabeled ex.: only features, like: {features, ?}: (x,?)
  - We use the model once it's done training w/ labeled examples to predict the label on unlabeled examples.
- Training: creating or learning the model.
  - Show the model (x, y) such that it can learn the relationships btw. feature x and label y such that prediction $\hat{y}$ is sufficiently close to the label y.
- Inference: means applying the trained model to unlabeled examples (making useful predictions $\hat{y}$)
- Regression model: predicts continuous vals. (numerical)
- Classification model: predicts discrete vals. (descriptive)

2.b. Slide Notes

- Linear regression: finding the relationship of data through the formula $y = mx + b$
- ML equation is slightly different w/ $\hat{y} = b + w_1 x_1$, where:
  - $\hat{y}$: predictied label (desired output), b is the bias (y-int.) [also called w_o], w_1 is the weight of feature 1 [weight is similar to slope m], and x_1 is a feature (known input).
- To infer (predict) $\hat{y}$ for a new val. x_1, just substitute x_1 val. into this model.
  - Bigger models would rely on multiple features $x_1, x_2, \ldots, x_n$, each having seperete weights $w_1, w_2, \ldots, w_n$.
    - For example: a model w/ three features might look like: $\hat{y} = b + w_1 x_1 + w_2 x_2 + w_3 x_3 = b + \sum_{j=1}^{3} w_j x_j$.

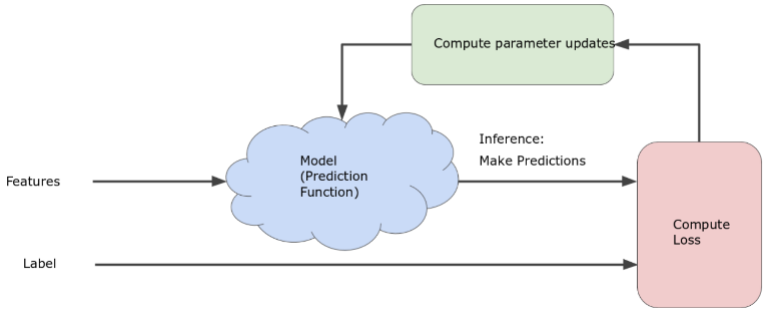
2.c. Slide Notes

- Training: examining the examples and adjusting the weights & bias so that the loss is minimized.
- Loss: penalty for a bad prediction, quantifying how bad the model's prediction was on a single example.
- The goal of training: finding a set of weights & biases that have low loss across all examples on average (process called empirical risk minimization).
- Use of a square loss employed as a loss function (also known as a L_2 loss).
  - If we let $w = (b, w_1, \ldots, w_n)$ be the params. of the model (weights and bias), and features be w/ $x = (x_1, \ldots, x_n)$ label y, the model will predict $\hat{y} = f_w(x) = b + \sum_{j=1}^{n} w_j x_j$.
    - The squared loss for a single example the difference btw. label (obs.) y and prediction $\hat{y}$: $(y - \hat{y})^2$.
- Mean square error (MSE): average squared loss per example over whole dataset: $MSE(w) = 1/m \sum_{i=1}^{m} (y^{(i)} - \hat{y}^{(i)})^2$.
  - m is the number of examples, $x^{(i)} = (x_1^{(i)}, \ldots, x_n^{(i)})$ & $y^{(i)}$ are the features and the label of the ith example, and $\hat{y}^{(i)}$ is the prediction of the model.
    - Formally, $\hat{y} = f_w(x^{(i)}) = b + \sum_{j=1}^{n} w_j x_j^{(i)}$.

    Although MSE is heavily used in ML, it isn't the best loss function or the the only practical loss function for every circumstance.

2.d. Slide Notes

- Iterative learning: try to reduce loss iteratively (guess a val. of w_1 and wait for the system to tell us what the loss is)
- If we adapt the weights correctly, we will be decreasing the loss over time. The challenge is to find the best possible model as efficiently as possible.
  - The iterative trial-and-error process that ML algos. use to train a model includes:



- Iterative strats. are prevalent in ML because they scale so well to large data sets. The model takes features $x_1, \ldots, x_n$ as input and returns one prediction $\hat{y}$ as output.
  - If we consider that the simplest lin. reg. model that takes only one feature as input: $\hat{y} = b + w_1 x_1$. For lin. reg. problems, we can pick random vals. for the starting positions b & w_1.
- If we look inside the "Compute parameter updates" part of the diagram, we can see the ML system examines the val. of the loss function & generates new vals. for b & w_1. We can say for now that it devises new vals. & then the ML system re-evaluates all those features against all those labels, yielding a new val. for the loss function, which yields new param. values. The learning continues iterating until the ML system discovers the model params. w/ the lowest possible loss. Usually, we iterate until the loss stops changing or at least there are extremely slow changes to the model. If this happenes, we can say the model has converged.
- A ML model is trained by starting w/ an init. guess for the weights & bias and iteratively adjusting those guesses until finding the weights & the bias w/ the lowest possible (or sufficiently low) loss are found.

2.e. Slide Notes

- Gradient descent algo.: When we consider the linear regression model $\hat{y} = f_w(x) = b + w_1 x_1 + w_2 x_2 + \ldots + w_n x_n$, where $w = (w_0, w_1, \ldots, w_n)$, The loss function (MSE):
$$\mathcal{L}\colon \mathbb{R}^{n+1} \to \mathbb{R}$$
depends on the params. $n+1$ params. $b, w_1, \ldots, w_n$. The loss is given by:
$$\mathcal{L} = 1/m \sum_{i=1}^{m} 1/2(\hat{y}^{(i)} - y^{(i)})^2$$
$$= 1/m \sum_{i=1}^{m} 1/2(f_w(x^{(i)} - y^{(i)}))^2$$
$$= 1/m \sum_{i=1}^{m} 1/2(\sum_{j=1}^{n} w_j x_j + b - y^{(i)})^2.$$
- For $n = 1$, the loss function $\mathcal{L}$ depends on two params., the bias term $b = w_0$ and the weight w_1, & defines a surface in 3D. For $n > 1$, the loss function $\mathcal{L}$ cannot be visualized easily. To simplify the plots, we assume that $n = 1$ and the bias term $b = w_0$ is fixed to be 0. Then the loss function $\mathcal{L}$ depends only on w_1 and defines a curve.
- The resulting plot of the loss function $\mathcal{L}$ is convex (assuming graph is loss over value of weight w_1). Even in the general case, the loss function $\mathcal{L}$ is convex. This is important since problems only have one min. Calculating the loss function for all param. values $w_0, \ldots, w_n \in \mathbb{R}^{n+1}$ would be an inefficient way of finding the min. Let's examine a better mechanism (very pop. in ML) called gradient descent.

- The starting point doesn't matter in the first stage in gradient descent, so we can set $w_i = 0$ or a rand. val.
- The gradient descent algo. then calculates the gradient of the loss function $\mathcal{L}$ at the starting point. The gradient $\nabla\mathcal{L} \in \mathbb{R}^{n+1}$ is a vector entries $(\nabla\mathcal{L})_i$ are given by the partial derivs. $\partial\mathcal{L}/\partial w_i$ of the loss function $\mathcal{L}$ with respect to the weights w_i.
- The $\nabla\mathcal{L}$ gradient has both a dir. and a mag. The graident points which way is closer or farther from the intended target. The gradient always points in the dir. of steepest increase in the loss function. For the case $n = 1$ & the bias $w_0 = b$ is fixed to be 0, the gradient of the loss function $\mathcal{L}$ is simply the slope of the curve $\mathcal{L}$, that is, the deriv. w/ respect to w_1.
  - The gradient descent algo. takes a step in the direction of the negative gradient $-\nabla\mathcal{L}$ to reduce the loss. More precisely, the gradient descent algo. updates the starting point as follows: w $\leftarrow$ w $-\alpha\nabla\mathcal{L}$, where α is the learning rate.
- The gradient vector also has both a dir. & a mag. The gradient descent algo. multiplies the grad. by a scalar known as the learning rate (also sometimes called step size) to determine the next point. The learning rate is a so-called hyperparameter: a parameter that is external to the model.
  - If the learning rate is too small, learning will take too long, but if it is too large, the next point will perpetually bounce haphazardly across the bottom of the well. There must be a Goldilocks learning rate for every linear reg. problem.

Python3 Notes

- Primitive Datatypes – straighforward
- Control Statements (if, for, while, etc.) – remember to add ":" after statements and to indent

Effect of Learning Rate on Gradient Descent for Finding Minima of Univariate Functions Notes

- N/A